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A Model for Directional Hurricane Wind Speeds

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1 Introduction

Let $\boldsymbol{X}$ be an $\mathbb{R}^d$-valued random variable whose coordinates $\{X_i\}$, $i = 1, \ldots, d$, denote hurricane wind speeds in d-directions at a site. Independent samples of $\boldsymbol{X}$ can be viewed as synthetic hurricane wind speeds occurring in different storms. The random vector $\boldsymbol{X}$ cannot be Gaussian since the sequence of wind speeds recorded in an arbitrary direction $i = 1, \ldots, d$ during different storm has 0's so that the marginal distribution of X_i has a finite mass at 0.

Our objectives are to develop (1) a probabilistic model for $\boldsymbol{X}$ describing hurricane wind speeds in 16 directions at angles $\theta_i = 22.5^o\,(i-1)$, $i = 1, \ldots, 16$, where θ_1 corresponds to North, (2) a method for calibrating the model for $\boldsymbol{X}$ to records available at a site, and (3) a Monte Carlo algorithm for generating synthetic hurricane speeds over an arbitrary number of years a selected site.

2 Probability law of hurricane wind speed

Consider the special case in which the coordinates of $\boldsymbol{X}$ are Bernoulli random variables, that is,

$$X_i = \begin{cases} 0, & \text{probability } 1 - p_i \\ 1, & \text{probability } p_i, \end{cases} \tag{1}$$

where $p_i \in (0,1)$ for $i = 1, \ldots, d$. The values 0 and 1 of a coordinate X_i of $\boldsymbol{X}$ correspond to 0 and non-zero hurricane wind speeds in direction $i = 1, \ldots, d$. The average number of 0's and 1's of X_i in n independent trials are $n\,(1-p_i)$ and $n\,p_i$, respectively. We use the model in Eq. 1 to illustrated difficulties related to the complete probabilistic characterization of the hurricane wind vector $\boldsymbol{X}$.

If the coordinates of $\boldsymbol{X}$ are independent, Eq. 1 defines the probability law of $\boldsymbol{X}$. If the coordinates of $\boldsymbol{X}$ are dependent, additional information is needed to specify $\boldsymbol{X}$. Let $p_{k_1,\ldots,k_d} = P\big(\cap_{i=1}^d \{X_i = k_i\}\big)$ with $k_1, \ldots, k_d \in \{0,1\}$ denote the probability that $\big(X_1, \ldots, X_d\big)$ is equal to a particular string $\big(k_1, \ldots, k_d\big)$ of 0's and 1's. We note that (1) the probabilities $\{p_{k_1,\ldots,k_d}\}$, $k_1, \ldots, k_d \in \{0,1\}$, define uniquely the probability law of $\boldsymbol{X}$ and (2) $p_{k_1,\ldots,k_d} = \prod_{i=1}^d P\big(X_i = k_i\big)$ if $\boldsymbol{X}$ has independent coordinates.

The complete characterization of $\boldsymbol{X}$ involves two types of difficulties. First, the number of probabilities $\{p_{k_1,\ldots,k_d}\}$ defining the probability law of $\boldsymbol{X}$ increases rapidly with d. For example, suppose that $d = 3$. The probability law of $\boldsymbol{X}$ is completely defined by $2^d = 8$

probabilities $p_{k_1,k_2,k_3} = P\big(X_1 = k_1, X_2 = k_2, X_3 = k_3\big)$, $k_1, k_2, k_3 \in \{0, 1\}$, that the vector $\big(X_1, X_2, X_3\big)$ is equal to $(0,0,0)$, $(1,0,0)$, $(0,1,0)$, $(0,0,1)$, $(1,1,0)$, $(1,0,1)$, $(0,0,1)$, and $(1,1,1)$. The number of probabilities $\{p_{k_1,\ldots,k_d}\}$ is 8; 32; 1,024; and 65,536 for $d = 3$; 5; 10; and 16, respectively. Numerical calculations involving 65,536 probabilities are not feasible. Second, the probabilities $\{p_{k_1,\ldots,k_d}\}$ need to be estimated from data. Estimates of these probabilities are likely to be unreliable or even impossible for vectors $\boldsymbol{X}$ with dimension $d = 8$ or larger if based on records of typical length. These considerations demonstrate the need for developing simplified models for $\boldsymbol{X}$ that are numerically tractable and their parameters can be estimated reliably from data.

3 Translation model for hurricane wind speeds

We propose a translation non-Gaussian model $\boldsymbol{X}_T$ for the wind speed vector $\boldsymbol{X}$, present a method for estimating the probability law of $\boldsymbol{X}_T$, and develop a Monte Carlo algorithm for generating samples of $\boldsymbol{X}_T$.

3.1 Model definition

Let p_i and F_i denote the probability that the coordinate X_i, $i = 1, \ldots, d$, of $\boldsymbol{X}$ is not 0 and the distribution of the non-zero values of this coordinate, so that

$$\tilde{F}_i(x) = (1 - p_i)\, 1\big(x \geq 0\big) + p_i\, F_i(x), \quad i = 1, \ldots, d, \tag{2}$$

is the distribution of X_i, where $1(A) = 1$ and 0 if statement A is valid and invalid, respectively. We can view X_i as a generalized Bernoulli variable that is 0 with probability $1 - p_i$ and is a random variable following the distribution F_i with probability p_i

Consider an $\mathbb{R}^d$-valued random variable $\boldsymbol{X}_T$ with coordinates $X_{T,i}$ defined by

$$X_{T,i} = \tilde{F}_i^{-1}\big(G_i\big), \quad i = 1, \ldots, d, \tag{3}$$

where $\boldsymbol{G} = (G_1, \ldots, G_d)$ is a standard $\mathbb{R}^d$-valued Gaussian variable, that is, Mean$[G_i] = 0$, Var$[G_i] = 1$, and Covariance$[G_i, G_j] = \rho_{ij}$, $i = 1, \ldots, d$. We refer to $\boldsymbol{X}_T$ as the translation model for $\boldsymbol{X}$. The model $\boldsymbol{X}_T$ has the same marginal distributions as $\boldsymbol{X}$ irrespective of the covariance matrix $\boldsymbol{\rho} = \{\rho_{ij}\}$ of $\boldsymbol{G}$ since $X_{T,i}$ is 0 with probability $P\big(\Phi(G_i) \leq 1 - p_i\big) = P\big(G_i \leq \Phi^{-1}(1 - p_i)\big) = 1 - p_i$ and has distribution F_i with the complement of this probability, that is, $P\big(X_i \neq 0\big) = p_i$ for all $i = 1, \ldots, d$. The dependence between the coordinates of $\boldsymbol{X}_{T,i}$ is defined by the covariance matrix $\boldsymbol{\rho}$ of $\boldsymbol{G}$ and the marginal distributions $\{F_i\}$ of $\boldsymbol{X}$. The relationship between the correlation structures of $\boldsymbol{G}$ and $\boldsymbol{X}_T$ is discussed in [1] (Section 3.1.1).

The translation model in Eq. 3 has two notable features. The model (1) has, as already stated, the same marginal distributions as $\boldsymbol{X}$ and (2) is sufficiently simple to be used in applications. A limitation of the model is that the complex dependence between the coordinates of $\boldsymbol{X}$ is represented approximately.

3.1.1 Parameter estimation

Let $(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ be n independent samples of $\boldsymbol{X}$, and let $(x_{i,1}, \ldots, x_{i,n})$ denote the corresponding n samples of coordinate X_i, $i = 1, \ldots, d$. Denote by $(y_{i,1}, \ldots, y_{i,m_i})$, $m_i \leq n$, the sequence of non-zero readings extracted from $(x_{i,1}, \ldots, x_{i,n})$. For example, $x_{i,1}$ is not included in $(y_{i,1}, \ldots, y_{i,m_i})$ if 0 and $y_{i,1} = x_{i,1}$ if $x_{i,1} \neq 0$.

The probabilities p_i and the marginal distributions F_i can be estimated by

$$p_i \simeq \hat{p}_i = \frac{m_i}{n}, \quad i = 1, \ldots, d, \tag{4}$$

and

$$F_i(x) \simeq \hat{F}_i(x) = \frac{\sum_{j=1}^{m_i} 1(y_{i,j} \leq x)}{m_i}, \quad i = 1, \ldots, d. \tag{5}$$

Similarly, the mean μ_i and variance σ_i^2 of F_i can be estimated from

$$\begin{aligned} \mu_i &\simeq \hat{\mu}_i = \frac{1}{m_i} \sum_{j=1}^{m_i} y_{i,j} \\ \sigma_i^2 &\simeq \hat{\sigma^2}_i = \frac{1}{m_i} \sum_{j=1}^{m_i} \left(y_{i,j} - \hat{\mu}_i\right)^2. \end{aligned} \tag{6}$$

The estimation of the correlation matrix $\boldsymbol{r} = \{r_{ij}\}$, $i, j = 1, \ldots, d$, corresponding to non-zero values of $\boldsymbol{X}$ poses some difficulties since different coordinates of $\boldsymbol{X}$ may be non-zero in different storms. Two options have been considered. First, select from the available record $(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ only those storms in which all coordinates are non-zero. This option is not viable since data shows that the resulting sample can be so short that reliable estimates of $\boldsymbol{r}$ are not possible. Second, select from the available record $(\boldsymbol{x}_1, \ldots, \boldsymbol{x}_n)$ all storms in which the entries of a particular pair (i, j) of coordinates are not zero and estimate r_{ij} from this record. The advantage of this approach is that allows more reliable estimates of $\boldsymbol{r}$. A potential problem is that the resulting estimate $\hat{\boldsymbol{r}}$ of $\boldsymbol{r}$ may not be positive definite. We present in the following section a procedure for handling this situation. Let $\hat{\boldsymbol{\zeta}}$ be the estimate of the matrix of correlation coefficients of the non-zero values of $\{X_i\}$ obtained from $\hat{\boldsymbol{r}}$ and Eq. 6. Since the differences between the correlation matrices $\boldsymbol{\rho}$ of the Gaussian image $\boldsymbol{G}$ of $\boldsymbol{X}_T$ and $\boldsymbol{\zeta}$ are not significant for positively correlated random variables ([1], Section 3.1.1), we approximate $\boldsymbol{\rho}$ by $\hat{\boldsymbol{\zeta}}$.

3.2 Monte Carlo algorithm

Suppose we need to generate n independent samples of $\boldsymbol{X}$. The proposed algorithm uses samples of $\boldsymbol{X}_T$ as a substitute for samples of $\boldsymbol{X}$, and involves the following two steps.

Step 1. Generate n independent samples $(\boldsymbol{g}_1, \ldots, \boldsymbol{g}_n)$ of $\boldsymbol{G}$ with mean $\boldsymbol{0}$ and covariance matrix $\hat{\boldsymbol{\zeta}}$.

Step 2. Calculate samples $(\boldsymbol{x}_{T,1}, \ldots, \boldsymbol{x}_{T,n})$ of $\boldsymbol{X}_T$ from $(\boldsymbol{g}_1, \ldots, \boldsymbol{g}_n)$ and Eq. 3, and plot the resulting samples. It is assumed that all F_i are reverse Weibull distributions.

As previously stated, the generation of samples of $\boldsymbol{G}$ may pose some difficulties since the estimate $\hat{\boldsymbol{r}}$ of the correlation matrix $\boldsymbol{r}$, and consequently the estimate $\hat{\boldsymbol{\zeta}}$ of $\boldsymbol{\zeta}$, may not be positive definite. The generation algorithm is based on the approximate representation

$$\boldsymbol{G} \simeq \tilde{\boldsymbol{G}} = \sum_{k=1}^{16} \nu_k^* V_k \boldsymbol{\phi}_k \tag{7}$$

of $\boldsymbol{G}$, where $\{V_k\}$ are independent Gaussian variables with mean 0 and variance 1, $\{\nu_k, \boldsymbol{\phi}_k\}$ denote the eigenvalues and the eigenvectors of $\hat{\boldsymbol{\zeta}}$, and $\nu_k^* = \nu_k$ if $\nu_k > 0$ and $\nu_k^* = 0$ otherwise. We use the approximation in Eq. 7 to generate samples of $\boldsymbol{G}$.

4 MATLAB functions

Two MATLAB functions have been developed,

hurricane_dir_est.m and
hurricane_dir_mc.m.

The first function estimates the parameters of the probability law of $\boldsymbol{X}_T$. The second function generate samples of $\boldsymbol{X}_T$. The dimension of $\boldsymbol{X}$ is $d = 16$.

4.1 MATLAB function hurricane_dir_est.m

The input consists of:

(1) A record at a specified milepost (see lines 23 to 27),

(2) A range [cmin, cmax] of Weibull tail parameter c and the number nc of intervals in [cmin, cmax]. We note that cmax needs to be selected to avoid unrealistic tail parameters. It is suggested to set cmax = 10, and

(3) A minimum number ncorr of non-zero pairs of non-zero readings needed to estimate entries of $\boldsymbol{\zeta}$. If ncorr is not reached for a pair (i, j), we set $\hat{\zeta}_{ij} = 0$. It is suggested to set ncorr = 10.

The output consists of:

(1) Estimates of the probabilities p(i) = $P(X_i = 0)$, $i = 1, \ldots, d$,

(2) Estimates of reverse Weibull parameters alpha1(i), c(i), and xi(i), $i = 1, \ldots, d$,

(3) Estimates zeta1(i, j) of the correlation coefficients ζ_{ij}, $i, j = 1, ..., d$, and

(4) Plots with estimates of the probabilities p_i; mean, standard deviation, skewness of non-zero values of X_i; estimates of the correlation coefficients of all data and of non-zero data; estimates of the parameters of the reverse Weibull distributions; and histograms of non-zero readings in all directions including Weibull densities fitted to these data.

The above output needs to be saved in a file for use in **hurricane_dir_mc.m**. The command **save estimates350 p zeta1 alpha1 c xi** may be used to store parameters needed for simulation. It is suggested that the file name be related to milepost number, for example, **estimates350** if dealing with milepost350.

4.2 MATLAB function hurricane_dir_mc.m

The input consists of:

(1) A file with estimates of the parameters needed to define the probability law of $\boldsymbol{X}_T$, for example, the file **estimates350** and

(2) The sample size ns and a seed nseed for sample generation.

The output consists of:

(1) Three dimensional plots of the generated samples of $\boldsymbol{G}$ and

(2) Three dimensional plots and contour lines of the generated samples of $\boldsymbol{X}_T$.

5 Conclusions

A non-Gaussian model has been developed for hurricane wind speeds recorded in 16 equally spaced directions based on the theory of translation variables. A method has been presented for calibrating the wind model to site records. The calibrated model has been used to generate synthetic hurricane wind speeds of arbitrary length at a selected site.

References

[1] M. Grigoriu. *Applied Non-Gaussian Processes: Examples, Theory, Simulation, Linear Random Vibration, and MATLAB Solutions.* Prentice Hall, Englewoods Cliffs, NJ, 1995.

Appendix A. MATLAB function hurricane_dir_est.m

```
function [p,mu,sig,gam3,zeta_t,zeta1,alpha1,c,xi] = ...
    hurricane_dir_est(cmin,cmax,nc,ncorr)
%
%   It estimates:
%       (1) The probability p(i)=P(X_i=0) that coordinate
%           i=1,...,16 of wind speed is 0
%       (2) The mean mu(i), standard deviation sig(i), and
%           skewness coefficient gam3(i) of the non-zero
%           values for each i=1,...,16
%       (3) The correlation coefficients {zeta_t(i,j)},
%           i,j=1,...,16, of the complete record,
%           i.e., including zero readings, and
%           {zeta1(i,j)}, i,j=1,...,16, of
%           non-zero readings
%------------------------------------------------------------------
%   INPUT:  (1) A record at a specified milepost
%               (see lines 23 to 27)
%           (2) Range [cmin,cmax] of Weibull tail
%               parameter c and nc = # of intervals
%               in [cmin,cmax]
%               NOTE:  cmax is also used to limit the value
%                      of the tail parameter, eg, cmax=10
%           (3) ncorr = the minimum number of non-zero
%               readings for which correlation is calculated
%               If ncorr is not reached, the correlation
%               coefficient is set 0
%               (Suggestion: Set ncorr=10)
%----------------------------------------------------------------
%   OUTPUT: (1) Estimates of {p(i)}, i=1,...,16
%           (2) Estimates of reverse Weibull parameters
%               {alpha1(i), c(i), xi(i)}, i=1,...,16
%           (3) Estimates of the correlation coefficients
%               {zeta1(i,j)}, i,j=1,...,16, corresponding
%               non-zero wind speeds
%=================================================================
%   Load record = a (999,17)-matrix for a Milepost
%           NOTE: THE FOLLOWING INSTRUCTION HAS TO BE MODIFIED
%                 TO SELECT A DIFFERENT MILEPOST #
%-------------------------------------------------------------
load  milepost350;
q=matrix;
nr=length(q(:,1));
nu=mean_rate;   %  nu = the average number of hurricane/year
%                     also in hppt://www.nist.gov/wind
%=============================================================
%   Estimates of probabilities p(i)
%   NOTE:  All readings are >=0
%-------------------------------------------------------------
for i=1:16,
    p(i)=sum(q(:,i)>0)/nr;
end,
figure
plot(1:16,p)
```

```
xlabel('Wind direction')
ylabel('Estimates of probabilities of non-zero values')
%------------------------------------------------------------
%   Construct non-zero wind speed records in each
%   direction, estimate {mu(i), sig(i), gam3(i)}, and
%   calculte coeffiicents of variation vq(i)=sig(i)/mu(i)
%------------------------------------------------------------
for i=1:16,
    nnz=0;
    for kr=1:nr,
        if q(kr,i)>0,
            nnz=nnz+1;
            xnz(nnz)=q(kr,i);
        end,
    end,
    xnzz=xnz(1:nnz);
    mu(i)=mean(xnzz);
    sig(i)=std(xnzz);
    vq(i)=sig(i)/mu(i);
    gam3(i)=mean(((xnzz-mu(i))/sig(i)).^3);
end,
figure
plot(1:16,mu,1:16,sig,':')
xlabel('Wind direction')
ylabel('Estimates of mean/std (solid/dotted lines) for non-zero values')
figure
plot(1:16,gam3)
xlabel('Wind direction')
ylabel('Estimates of skewness for non-zero values')
%------------------------------------------------------------
%   Estimates of correlation coefficients
%   {zeta_t(i,j)},  i,j=1,...,16
%------------------------------------------------------------
qq=q(:,1:16);
zeta_t=corrcoef(qq);
figure
mesh(1:16,1:16,zeta_t)
xlabel('Wind direction #')
ylabel('Wind direction #')
zlabel('Estimates of correlation coefficients \zeta_t')
%------------------------------------------------------------
%   Estimates of correlation coefficients
%   {zeta(i,j)},  i,j=1,...,16
%------------------------------------------------------------
for i=1:16,
    for j=1:16,
        q1=q(:,i);
        q2=q(:,j);
        nqq=0;
        for kr=1:nr,
            if q1(kr)>0 & q2(kr)>0,
                nqq=nqq+1;
                xqq(nqq,:)=[q1(kr) q2(kr)];
            end,
        end,
        if nqq<=01,
            zeta(i,j)=0;
```

```
        else,
            rr=corrcoef(xqq(1:nqq,1),xqq(1:nqq,2));
            rrr=rr(1,2);
            zeta(i,j)=rrr;
        end,
    end,
end,
figure
mesh(1:16,1:16,zeta)
xlabel('Wind direction #')
ylabel('Wind direction #')
zlabel('Estimates of correlation coefficients \zeta')
figure
contour(1:16,1:16,zeta)
xlabel('Wind direction #')
ylabel('Wind direction #')
title('Estimates of correlation coefficients \zeta')
%==========================================================================
%   Estimates of the paramters of reverse Weibull distributions
%   fitted to non-zero wind speeds (Method of moments)
%   USE [- RECORD] in all directions
%--------------------------------------------------------------------------
%           Relationship between Weibull tail parameter
%           and skewness
%--------------------------------------------------------------------------
dc=(cmax-cmin)/nc;
cc=cmin:dc:cmax;
lc=length(cc);
g1=gamma(1./cc+1);
g2=gamma(2./cc+1);
g3=gamma(3./cc+1);
skew=(g3-3*g1.*g2+2*g1.^3)./(g2-g1.^2).^(3/2);
% figure
% plot(cc,skew)
% xlabel('coefficient c')
% ylabel('skewness')
%--------------------------------------------------
%           Calculation of skewness coefficients
%           for values of c>0 in [cmin,cmax]
%           and estimated tail parameters
%           {c(i)}, i=1,...,16
%----------------------------------------
for i=1:16,
    muw(i)=-mu(i);
    sigw(i)=sig(i);
    gamw3(i)=-gam3(i);
    c(i)=interp1(skew,cc,gamw3(i),'spline');
    %----------------------------------------------
    %   NOTE:  This condition is needed since
    %          c can take very large values
    %----------------------------------------------
    if c(i)>cmax,
        c(i)=cmax;
    end,
end,
%------------------------------------------------------
%           NOTE: If desired one or more or all c(i)'s
```

```
%                    can be assigned different values
%-----------------------------------------------------------
for i=1:16,
    ggw1(i)=gamma(1./c(i)+1);
    ggw2(i)=gamma(2./c(i)+1);
    ggw3(i)=gamma(3./c(i)+1);
    alpha(i)=sigw(i)/sqrt(ggw2(i)-ggw1(i)^2);
    xi(i)=muw(i)-alpha(i)*ggw1(i);
end,
figure
plot(1:16,alpha,1:16,c,':',1:16,xi,'--')
xlabel('Wind direction #')
ylabel('Reverse Weibull parameters for non-zero readings')
title('Estimates of \alpha, c, and \xi (solid, dotted, and dashed lines)')
%------------------------------------------------------------------------------
%   Plots of histograms and fitted reverse Weibull distributions
%   to non-zero wind speeds in all directions
%------------------------------------------------------------------------------
for i=1:16,
    nnz=0;
    for kr=1:nr,
        if q(kr,i)>0,
            nnz=nnz+1;
            xnz(nnz)=q(kr,i);
        end,
    end,
    xnzz=xnz(1:nnz);
    figure
    hist_est(xnzz',1,30)
    hold
    yxi=xi(i):.1:50;
    yw=(yxi-xi(i))/alpha(i);
    fw=(c(i)/alpha(i))*(yw.^(c(i)-1)).*exp(-yw.^c(i));
    plot(-yxi,fw)
    xlabel('Wind speed (mph)')
    ylabel(['Direction ' int2str(i)])
    %   print
end,
zeta1=zeta;
alpha1=alpha;
%===============================================================================
%   EXAMPLE:
%   [p,mu,sig,gam3,zeta_t,zeta1,alpha1,c,xi]=hurricane_dir_est(.1,10,1000,10);
%   NOTE: Save the output needed for Monte Carlo simulation, e.g., use
%         save estimates350 p zeta alpha c xi
%         (estimates350 = file name, 350 since mileplot350 is used)
```

Appendix B. MATLAB function hurricane_dir_mc.m

```
function [thurr,xrw_mc,xrw_mc_ind,xrws_mc,xrws_mc_ind] = ...
    hurricane_dir_mc(nyr,cws,nseed)
%
%   INPUT FROM hurricane_dir_est.m ---> estimates1450_cw10 (for milepost1450),
%         and consists of estimtes of the parameters:
%
%               * (alpha1, cw, xi) of reverse Weibull distributions
%                 fitted to non-zero wind speeds in 16 direction.
%               * (alphas, xis) of reverse Weibull distributions
%                 fitted to non-zero wind speeds in 16 direction
%                 with imposed tail parameter cws = 10 (c = - 0.1)
%                 in all directions.
%               * p = 16-dimensional vector with probabilities
%                     p(i)=P(X_i>0) of non-zero wind speeds.
%               * zeta1 = (16,16) matrix of correlation coefficients
%                         for non-zero wind speeds.
%-------------------------------------------------------------------
%   OTHER INPUT:
%
%               * nyr = # of years required for simulation.
%               * nseed = Monte Carlo simulation seed.
%-------------------------------------------------------------------
%
%   OUTPUT:
%               * thurr = times of thunderstorms in nyr years.
%               * xrw_mc = generated wind speeds in 16 directions/nyr years
%                 using estimates of (alpha1, cw, xi), p(i), and zeta1.
%               * xrw_mc_ind = generated wind speeds in 16 directions/nyr years
%                 using estimates of (alpha1, cw, xi) and p(i) under the
%                 assumption that wind speeds in different directions
%                 are mutaully independent.
%               * xrws_mc = generated wind speeds in 16 directions/nyr years
%                 using estimates of (alphas, xis), p(i), and zeta1 for
%                 an imposed tail parameter cws = - 1/c.
%               * xrws_mc_ind = generated wind speeds in 16 directions/nyr years
%                 using estimates of (alphas, xis) and p(i) for an imposed
%                 tail parameter cws = - 1/c under the assumption that wind
%                 speeds in different directions are mutaully independent.
%==========================================================================
%
%   REASONS FOR THE INDEPENDENCE ASSUMPTION AND THE RECOMMENDATION OF
%   USING xrw_mc_ind; xrws_mc_ind RATHER THAN xrw_mc; xrws_mc
%
%       (1) Correlation coefficients of all data (including 0's) are
%           relatively small (maximum values are of order 0.7).
%       (2) Correlation coefficients between random variables with
%           finite probability mass at 0 provide limited information
%           on the relationship between these random variables.
%       (3) Estimates of the correlation coefficients of non-zero
%           wind speeds can lead to inconsistencies, e.g., consider
%           wind speed readings in 3 directions x(i,j), j=1,2,3,
%           each of length n = 1000, and suppose the readings
%           x(600:1000,1), x(1:400,2), x(800:1000,2), and x(1:600,3)
```

```
%           are zero.  The estimates of the correlation coefficients
%           of these records are rho(1,2) not=0 (records x(:,1) & x(:,2)),
%           rho(2,3) not=0 (records x(:,2) & x(:,3)), but rho(1,3)=0
%           (records x(:,1) & x(:,3)).
%
%=====================================================================
%   Load estimates delivered by hurricane_dir_est.m
%   for a selected milepost (here milepost1450)
%---------------------------------------------------------------------
%   load estimates350
load milepost1450
nu=mean_rate;
load estimates1450_cw10
nd=length(p);
%---------------------------------------------------------------
%   Total number of hurricanes in nyr years:
%       thurr = a vector with entries times at which
%               hurricanes occurr in nyr years
%       nhurr = # of hurricanes in nyr years
%---------------------------------------------------------------
rand('seed',nseed)
time=0;
ktime=0;
while time<=nyr,
    ktime=ktime+1;
    time=time-log(rand(1,1))/nu;
    thr(ktime)=time;
end,
nhurr=ktime-1;
thurr=thr(1:nhurr);
%---------------------------------------------------------------------
%   Set 0 the entries of the matrices in which generated wind
%   will be stores
%---------------------------------------------------------------------
xrw_mc=zeros(nhurr,16);
xrw_mc_ind=zeros(nhurr,16);
xrws_mc=zeros(nhurr,16);
xrws_mc_ind=zeros(nhurr,16);
%---------------------------------------------------------------------
%   Generation of nhurr independent samples of a 16-dimensional
%   standard Gaussian vector with covariance matrix zeta1
%---------------------------------------------------------------------
%           Construct an approximate spectral representation
%           for a correlated standard Gaussian vector with
%           covariance approximating zeta1
%---------------------------------------------------------------------
[vzeta,dzeta]=eig(zeta1);
ndd=0;
for kd=1:nd,
    if dzeta(kd,kd)>0,
        ndd=ndd+1;
        lamz(ndd)=dzeta(kd,kd);
        phiz(:,ndd)=vzeta(:,kd);
    end,
end,
%---------------------------------------------------------------------
%           Generate required Gaussian samples
```

```
%--------------------------------------------------------------------
randn('seed',nseed);
gg=zeros(nhurr,nd);
for ks=1:nhurr,
    rg=randn(1,ndd);
    for kdd=1:ndd,
        gg(ks,:)=gg(ks,:)+lamz(kdd)*rg(kdd)*phiz(:,kdd)';
    end,
end,
gg=cdf('normal',gg,0,1);
%----------------------------------------------------------------
% figure
% mesh(1:16,1:nhurr,gg)
% xlabel('Wind direction')
% ylabel('Sample number')
% zlabel('Gaussian image')
% xlim([1 16])
% set(gca,'xticklabel','')
% set(gca,'xtick',[1:16])
% set(gca,'xticklabel',[1:16])
% ylim([1 nhurr])
% set(gca,'yticklabel','')
% set(gca,'ytick',[1 10:10:nhurr])
% set(gca,'yticklabel',[1 10:10:nhurr])
% %   print
%===============================================================
%   Translation from Gaussian to reverse Weibull space
%   CASE 1: Estimates of (alpha1, cw, xi), p(i), and zeta1
%---------------------------------------------------------------
%       gg=cdf('normal',gg,0,1);
for ks=1:nhurr,
    for i=1:nd,
        if gg(ks,i)>=1-p(i),
            uu=(gg(ks,i)-(1-p(i)))/p(i);
            xrw_mc(ks,i)=-xi(i)-icdf('wbl',uu,alpha1(i),cw(i));
        end,
%         [ks i gg(ks,i) 1-p(i) xrw_mc(ks,i)]
%         pause
    end,
end,
%***********************************
%   UNDER INDEPENDENCE ASSUMPTION
%***********************************
for ks=1:nhurr,
    for i=1:nd,
        ur=rand(1,1);
        if ur>=1-p(i),
            uu=(ur-(1-p(i)))/p(i);
            xrw_mc_ind(ks,i)=-xi(i)-icdf('wbl',uu,alpha1(i),cw(i));
        end,
%         [ks i gg(ks,i) 1-p(i) xrw_mc_ind(ks,i)]
%         pause
    end,
end,
%----------------------------------------------------------------
%   Translation from Gaussian to reverse Weibull space
%   CASE 2: Estimates of (alphas, xis), p(i), and zeta1
```

```
%           for an imposed tail parameter cws = - 1/c
%-----------------------------------------------------------------
%    gg=cdf('normal',gg,0,1);
for ks=1:nhurr,
    for i=1:nd,
        if gg(ks,i)>=1-p(i),
            uu=(gg(ks,i)-(1-p(i)))/p(i);
            xrws_mc(ks,i)=-xis(i)-icdf('wbl',uu,alphas(i),cws);
        end,
%          [ks i gg(ks,i) 1-p(i) xrws_mc(ks,i)]
%          pause
    end,
end,
%************************************
%   UNDER INDEPENDENCE ASSUMPTION
%************************************
for ks=1:nhurr,
    for i=1:nd,
        ur=rand(1,1);
        if ur>=1-p(i),
            uu=(ur-(1-p(i)))/p(i);
            xrws_mc_ind(ks,i)=-xis(i)-icdf('wbl',uu,alphas(i),cws);
        end,
%          [ks i gg(ks,i) 1-p(i) xrws_mc_ind(ks,i)]
%          pause
    end,
end,
%------------------------------------------------------------------
% figure
% mesh(1:16,1:nhurr,xrw_mc)
% xlabel('Wind direction')
% ylabel('Sample number')
% zlabel('Simulated hurricane wind speeds')
% xlim([1 16])
% set(gca,'xticklabel','')
% set(gca,'xtick',[1:16])
% set(gca,'xticklabel',[1:16])
% ylim([1 nhurr])
% set(gca,'yticklabel','')
% set(gca,'ytick',[1 10:10:nhurr])
% set(gca,'yticklabel',[1 10:10:nhurr])
% %   print
%---------------------------------------------
% figure
% contour(1:16,1:ns,xrws_mc)
% xlabel('Wind direction')
% ylabel('Sample number')
% title('Simulated hurricane wind speeds')
% xlim([1 16])
% set(gca,'xticklabel','')
% set(gca,'xtick',[1:16])
% set(gca,'xticklabel',[1:16])
% ylim([1 nhurr])
% set(gca,'yticklabel','')
% set(gca,'ytick',[1 10:10:nhurr])
% set(gca,'yticklabel',[1 10:10:nhurr])
% %   print
```

```
% %-----------------------------------------------------------
% figure
% contour(1:16,1:ns,xweib)
% xlabel('Wind direction')
% ylabel('Sample number')
% title('Simulated hurricane wind speeds')
% xlim([1 16])
% set(gca,'xticklabel','')
% set(gca,'xtick',[1:16])
% set(gca,'xticklabel',[1:16])
% ylim([1 ns])
% set(gca,'yticklabel','')
% set(gca,'ytick',[1 10:10:ns])
% set(gca,'yticklabel',[1 10:10:ns])
% %   print
%-----------------------------------------------------------------------
%   [thurr,xrw_mc,xrw_mc_ind,xrws_mc,xrws_mc_ind]=hurricane_dir_mc(200000,10,123);
```